Optimized membrane fouling prediction and mitigation for improved water treatment: A review

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Abstract:- This review article presents recent advancements in membrane filtration technologies, particularly focusing on fouling mechanisms affecting reverse osmosis (RO) membranes. It presents a comprehensive analysis of various studies conducted over the past two decades, highlighting the complexities of membrane fouling caused by natural organic matter (NOM), particulate matter, and biofouling. The review also examines innovative modelling approaches to predict fouling behaviour, including the development of the Membrane Fouling Index-Ultrafiltration (MFI-UF) method and the application of advanced characterization techniques such as optical coherence tomography (OCT) and Near-Edge X-ray Absorption Fine Structure (NEXAFS) spectroscopy. Additionally, it discusses the effectiveness of pre-treatment strategies, including coagulation and flocculation in mitigating fouling and enhancing membrane performance. Finally, the integration of artificial intelligence (AI) in predicting fouling behaviour is also highlighted, with emphasis on its potential to optimize operational parameters in membrane systems.

Keywords:- Membrane, Fouling, Filtration, Prediction, mitigation, water treatment, Machine learning , Optimization technology, Reverse osmosis.

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1 Introduction

Membrane filtration is a crucial method for water treatment, particularly in the context of reverse osmosis (RO) processes. As global water scarcity intensifies, the demand for efficient and sustainable water purification methods has never been greater (Odumosu *et al*., 2014; Ajayi *et al.,* 2022). However, one of the significant challenges faced in membrane filtration is fouling, which can severely impact membrane performance and longevity. Fouling is the accumulation of particles or biological substances that reduces membrane performance by lowering the flow rate (flux) and increasing maintenance costs. It occurs when contaminants accumulate on or within membrane surfaces, leading to reduced permeate flux and increased operational costs.

This review focuses on the various fouling mechanisms affecting RO membranes, particularly those associated with natural organic matter (NOM), particulate matter, and biofouling. Recent studies have highlighted the interactions between different foulants and the membranes themselves, necessitating a deeper understanding of these processes to develop effective mitigation strategies. For instance, studies have shown that the presence of divalent cations can significantly influence fouling behaviour by altering the composition of fouling layers on membranes. Moreover, advancements in modelling techniques and characterization methods have provided new methodologies, approaches, and new insights into predicting fouling behaviour. The integration of artificial intelligence (AI) tools to forecast fouling dynamics presents a veritable avenue for optimizing operational parameters in membrane systems. This review aims to synthesize recent findings in membrane fouling research, evaluate innovative pre-treatment strategies, and discuss the implications for future water treatment applications. It contributes to the ongoing efforts to enhance membrane filtration technologies and ensure their sustainability in addressing global water challenges.

2 Membrane Filtration and Fouling Mechanisms

Membrane filtration is a separation process that uses a semi-permeable membrane to separate particles from liquids or gases, widely applied in water treatment, food processing, and pharmaceuticals. It is a process that selectively allows certain substances through a membrane while retaining others, and it is crucial in applications like water purification. Its effectiveness, however, is challenged by fouling which is the buildup of undesired substances on the membrane surface or within its pores, which reduces performance and efficiency. The steps involved in the formation process of membrane fouling is presented in Figure 1.

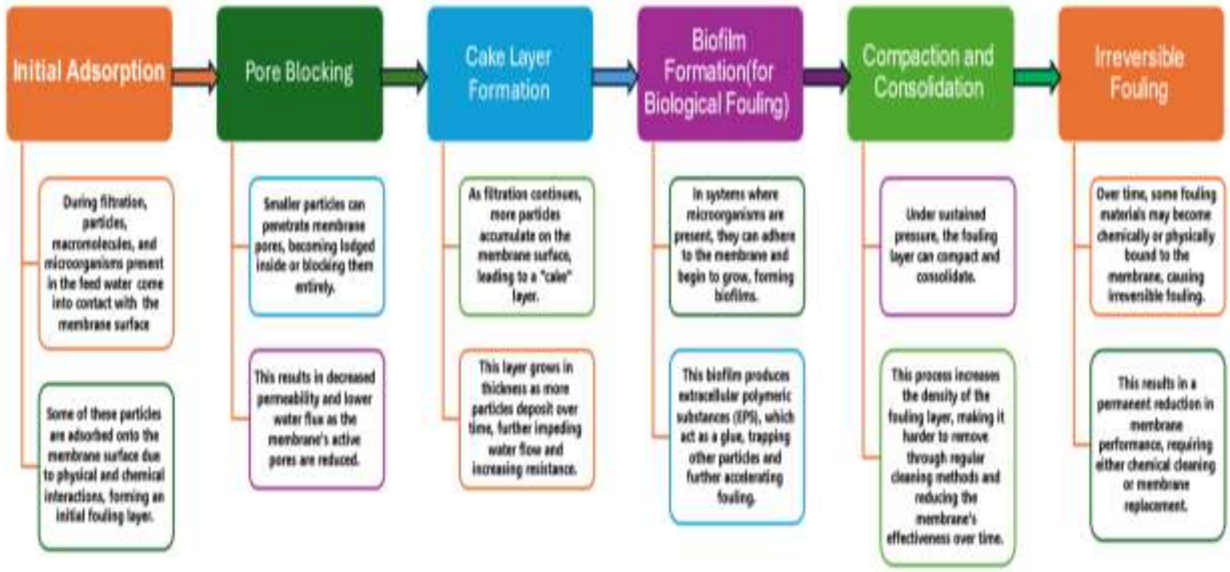

Figure 1: Steps involved in the formation process of membrane fouling

There are various types of fouling including (i) Particulate Fouling which is the formation of a solid particle layer (e.g., cake) that hinders flow, (ii) Biofouling which can be described as the growth of microorganisms like bacteria on the membrane thereby causing pressure issues and quality concerns, (iii) Organic Fouling which is the adsorption of natural organic matter (NOM) or model foulants, worsened by interactions with ions like calcium, and Scaling which is the deposition of inorganic salts (e.g., calcium carbonate), often requiring chemical cleaning (Lee *et al.*, 2016; Kim & Fane, 2018). AlSawaftah *et al.* (2022) also presented four types of fouling as shown in Figure 2.

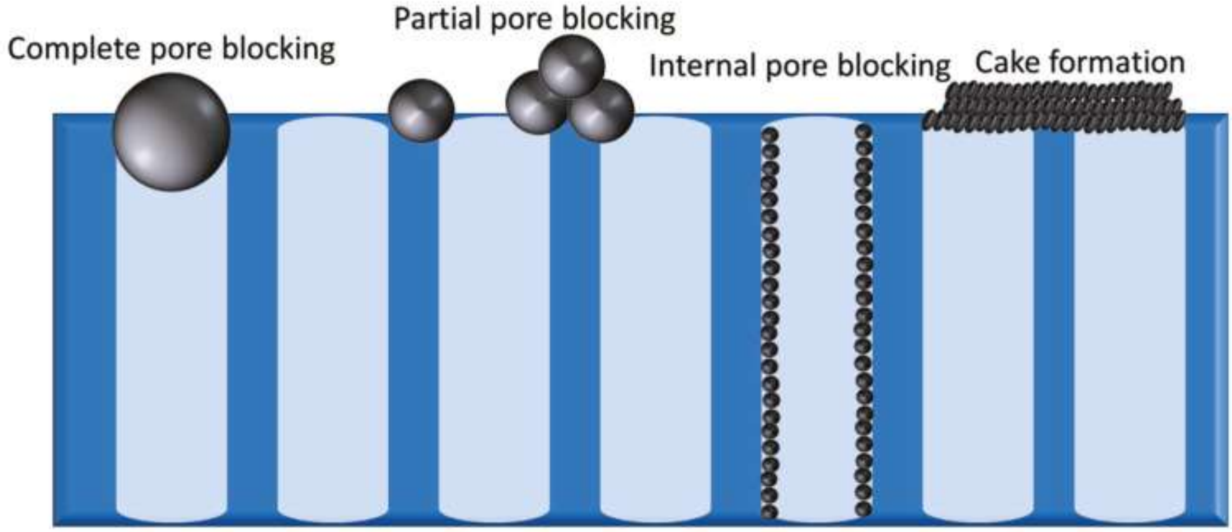

Figure 2: The four types of fouling (AlSawaftah *et al.*, 2022)

Xu, *et al.*, (2020) introduced an innovative analytical method using piecewise multiple linear regression to discern the dominant fouling mechanisms during membrane filtration. The article demonstrated how this method can effectively track changes in fouling behaviour over time, depending on the composition of the foulants present. This study enhances the overarching narrative of membrane fouling by providing tools to predict and manage fouling, which is crucial for maintaining high performance in membrane filtration systems.

Tong *et al.* (2020) reviewed fouling behaviour of organic matter on reverse osmosis (RO) and Nano filtration membranes over the past 19 years. Data on membrane flux changes over time were collected and analysed using mathematical models. The study conducted RO membrane fouling experiments using sodium alginate (SA), bovine serum albumin (BSA), and their mixture as foulants. The study also developed a time-course model to predict membrane fouling based on the concentration of foulants. The model was validated using experimental data, showing promising results. Additionally, the study investigated the interaction between SA and BSA and its effect on membrane fouling. The findings suggest that the developed model can accurately predict membrane fouling behaviour.

An investigation that focused on biofouling in a lab-scale reverse osmosis (LPRO) system using a model solution simulating the hydrolysis product of pig manure and sugar beet was conducted by Pratofiorito *et al.* (2022). The feed composition mainly consisted of acetate. The LPRO system had two flat sheet membrane modules (FMM) arranged in parallel, allowing for duplicate experiments. The modules were equipped with optical windows for visualization of fouling layers. Extra low Energy (XLE) membrane sheets were used in the modules. Operational conditions were maintained for 26 days with constant pressure and temperature. Optical coherence tomography (OCT) was used for imaging fouling development on both the membrane and spacer.

The results showed that fouling started on the spacer and then progressed to the membrane. Pressure drop in the feed channel increased steadily due to fouling on the spacer, with membrane fouling contributing later. Despite pressure drop, flux remained relatively stable until a significant decrease after 21 days. Surface coverage increased before membrane fouling thickness, suggesting irregular fouling distribution initially. The study concluded that OCT is effective for predicting pressure drop and flux decline and that membrane fouling thickness (ME) was found to be a better indicator of flux decline than surface coverage. The study also recommended that cleaning cycles should be initiated before maximum fouling on the spacer to prevent further deposition on the membrane.

Fortunato *et al.* (2021) explored the multifaceted challenges of fouling in membrane filtration systems, particularly in high-demand applications like seawater desalination and wastewater treatment. It discussed how fouling not only decreases membrane efficiency but also increases operational costs due to higher energy consumption and frequent maintenance needs. The article highlights recent innovations in fouling mitigation, such as the use of advanced membrane materials that resist fouling and innovative cleaning techniques that can be employed during operation. This complements the central theme of membrane filtration by emphasizing the necessity of addressing fouling to enhance operational reliability and longevity.

Abunada *et al.* (2023) investigated membrane particulate fouling mechanisms, particularly focusing on cake/gel filtration as the dominant mechanism in reverse osmosis (RO) membranes. To simulate this fouling mechanism, the Membrane Fouling Index-Ultrafiltration (MFI-UF) method was developed. It involves filtering feed water through an ultrafiltration (UF) membrane at constant flux to mimic RO conditions. The fouling index (I) is determined from the slope of the linear cake/gel filtration phase during MFI-UF testing and corrected to reference conditions. It also provides detailed descriptions of the methodology employed, including water sample collection, MFI-UF setup, membrane characteristics, flux rate determination, and fouling rate prediction. Additionally, the study discussed the correction of MFI-UF values for membrane surface porosity and the normalization of Net driving pressure (NDP) to accurately assess fouling rates. Finally, it compares predicted and observed fouling rates to validate the accuracy of the MFI-UF method in predicting particulate fouling in RO plants. MFI-UF measured directly at the same RO flux or extrapolated from higher flux rates yielded similar results, confirming the method's robustness. The comparisons of different approaches for MFI-UF measurement and found that extrapolation from three flux rate experiments with equal increments provided more accurate results. There was a linear correlation between MFI-UF and flux rate, although it might not hold true for all feed water types due to varying cake compressibility.

The study also revealed that the duration of MFI-UF tests depended on the applied flux rate, with higher flux rates requiring shorter test durations. Particle deposition factors (Ω) were examined, showing that smaller particles might detach from the RO membrane due to hydrodynamic conditions. Actual fouling observed in the RO plants indicated that particulate fouling was the main cause of Normalized Pressure Drop (NDP) increase, rather than scaling, biological, or organic fouling. Predictions of fouling rates using MFI-UF generally matched observed fouling rates, with the 100 kDa membrane providing the most accurate predictions. MFI-UF measurements with 5 kDa membranes tended to overestimate fouling rates, possibly because of membrane surface porosity. The study recommended that MFI-UF with 10–100 kDa membranes is suitable for predicting particulate fouling in RO plants.

Fouling in reverse osmosis (RO) membranes caused by natural organic matter (NOM) and model organic foulants (sodium alginate) in synthetic feedwaters was investigated by Landsman *et al.* (2023). The experiments aimed to understand the effects of major cations (Na+, Mg2+, Ca2+) and competing/synergistic fouling mechanisms. Two reference NOM samples were used, obtained through different extraction processes (RO and electrodialysis). Fouling experiments were conducted using a crossflow cell setup at elevated pressure and constant crossflow velocity. The BW30 membrane was used for the experiments, pre-conditioned with isopropyl alcohol and DI water. Characterization techniques included water quality analysis for NOM concentration and hydrophobicity, membrane fouling layer characterization through ICP-OES, X-ray absorption spectroscopy, resonant X-ray scattering, and wide-angle X-ray scattering. The results provided insights into the composition and structure of fouling layers, highlighting the role of organic and inorganic components in membrane fouling.

Moreover, the interaction between divalent cations and NOM alters the organic composition of fouling layers. In the presence of calcium and magnesium, hydrophobic, high molecular weight NOM compounds contribute more to membrane fouling, whereas sodium-induced fouling is not specific to NOM size or hydrophobicity.

Advanced characterization techniques, such as Near-Edge X-ray Absorption Fine Structure (NEXAFS) spectroscopy, reveal the organic composition of NOM fouling layers and the coordination of divalent cations within these layers. Calcium is found to form carboxyl complexes within and between NOM aggregates on membrane surfaces, leading to heterogeneous distribution of foulants.

Furthermore, in complex feedwaters containing calcium, alginate, and carbonate, alginate inhibits the growth of calcium carbonate (CaCO3) scales on the membrane surface, indicating synergistic interactions between different foulants.

In summary, the presence of divalent cations, particularly calcium, in natural organic matter (NOM) feed waters promotes significant fouling of reverse osmosis (RO) membranes. This fouling is attributed to the bridging of carboxyl groups in NOM by divalent cations, leading to flux decline during RO operation. The fouling behaviour differs between synthetic and natural NOM, with synthetic NOM causing less significant membrane fouling due to its higher hydrophilic content.

Yingcai *et al.* (2024) conducted experiments to understand membrane fouling in reverse osmosis (RO) systems caused by organic substances in wastewater effluents. The study used a specific RO membrane (Proc10) and fractionated the organic substances in the wastewater effluent into hydrophobic and hydrophilic fractions. Resin adsorption pre-treatment was employed to remove hydrophobic substances before subjecting the effluent to RO membrane treatment.

Hydrophobic organic substances (HOS) constituted a significant portion (50.0%-60.0%) of the dissolved organic carbon (DOC) in the source water, leading to substantial fouling of RO membranes. The reduction in RO membrane flux was primarily attributed to HOS, with hydrophilic organic nitrogen (HON) also contributing significantly to the flux decline. Hydrophobic/hydrophilic interactions played a crucial role in membrane fouling, with hydrophobic substances showing a stronger binding affinity to the membrane surface.

The XDLVO theory highlighted the higher adhesion energy and cohesion energy of SE, HOS, or HON on the RO membrane surface compared to hydrophilic substances, indicating stronger binding of hydrophobic pollutants to the membrane.

Resin pre-treatment effectively mitigated RO membrane fouling by selectively removing HOS from the source water. The concentration of HOS emerged as a novel indicator for assessing the inlet water quality of the RO system, with resin pre-treatment proving to be an effective method for HOS removal. The study established a flux prediction model for RO membrane based solely on the concentration of HOS in the source water which provides a practical tool for assessing membrane fouling potential.

Jang *et al.,* (2024) also focused on the filtration of greywater through porous membranes, revealing critical insights into the fouling mechanisms at play. It identifies that smaller pore sizes and higher pressures lead to more pronounced fouling, with three main mechanisms: complete pore blocking, intermediate pore blocking, and the formation of a cake layer on the membrane surface. By quantifying these mechanisms, the research provides a framework for understanding how varying water qualities can impact membrane performance. This directly relates to the discussion of fouling in membrane filtration, as it illustrates how different feedwater compositions can influence the efficiency of the separation process.

3 Membrane Filtration and Fouling Optimization

Optimization of membrane fouling and filtration is essential for enhancing the efficiency and durability of membrane-based separation processes used in water treatment applications, such as desalination and wastewater management. Fouling, which is the accumulation of unwanted materials on or within membrane surfaces, poses significant challenges, leading to reduced permeate flux, increased operational costs, and potential membrane failure (Hilal *et al.,* 2006).

Implementing techniques to reduce the concentration of contaminants before they reach the membrane, such as coagulation and flocculation, can significantly decrease fouling potential (Salazar-Peláez *et al.,* 2018). Studies have shown that effective pre-treatment can enhance permeate quality and reduce the frequency of cleaning (Hilal *et al.,* 2006). More details on pretreatment methods are presented in section 4.

Also, modifying flow rates, pressures, and chemical dosing can help maintain optimal conditions that minimize fouling (Salazar-Peláez *et al.,* 2018). For instance, adjusting the hydraulic retention time (HRT) in membrane bioreactor systems has been found to influence fouling rates significantly (Salazar-Peláez *et al.,* 2018).

Hilal *et al.* (2006) extensively reviewed the concept of membrane technology, covering various membranes, filtration modes, fouling mechanisms, and pre-treatment methods. Microfiltration (MF), Ultrafiltration (UF), and Nanofiltration (NF) membranes are discussed along with their pore sizes and separation capabilities. Fouling, a significant challenge in membrane processes, can be reversible or irreversible and is caused by substances accumulating on or within membranes.
The review also discussed the significance of backwashing and chemical cleaning in maintaining membrane performance over time. Coagulation and flocculation processes are highlighted for their role in wastewater treatment, particularly in removing colloidal material, enhancing permeate flux, and reducing membrane fouling.
Furthermore, the integration of coagulation with membrane filtration processes is examined for its effectiveness in removing NOM and improving water quality. Advanced oxidation processes (AOPs) and self-catalytic oxidation methods are explored for their potential in manganese removal from groundwater.

Nguyen *et al.* (2012) discussed the issue of biofouling in membrane filtration systems, which can severely compromise treatment efficiency. The authors highlighted that biofouling accounts for a substantial portion of membrane fouling, leading to decreased flux and increased energy consumption. They explored various monitoring and control strategies, including the use of biocides and physical cleaning methods, to manage biofouling effectively.

An experimental setup involving a Upflow Anaerobic Sludge Blanket (UASB) reactor coupled with an external Ultrafiltration (UF) membrane to treat wastewater was designed by Salazar-Peláez *et al.* (2018). The reactor was inoculated with sludge from a beverage industry and operated under different Hydraulic Retention Times (HRT). The membrane was subjected to constant pressure and cross-flow velocity during filtration cycles, followed by chemical cleaning. The fouling potential of the

UASB effluent was assessed using Silt Density Index (SDI), Modified Fouling Index (MFI), and a mathematical analysis based on a saturation curve model.
Obtained results showed that shorter HRT (4 hours) led to higher fouling potential compared to longer HRTs (8 and 12 hours), as indicated by lower flux and higher SDI and MFI values. Statistical analysis confirmed significant differences in fouling potential between different HRTs. The saturation curve model further supported these findings, revealing a proportional relationship between HRT and fouling potential.
The study concluded that operating the UASB reactor at shorter HRTs increases membrane fouling in the UF moule. While SDI and MFI tests were useful for predicting membrane fouling, with the saturation curve analysis provided clearer insights into the relationship between HRT and fouling potential. It also proved that operating the reactor under longer HRTs could mitigate membrane fouling in post-treatment UF modules.

Jepsen *et al.* (2018) focused on the mechanisms of fouling in seawater reverse osmosis (SWRO) systems, a critical technology for desalination. The authors identified key fouling contributors, including organic matter, inorganic scaling, and biofouling, and discuss various control strategies such as pre-treatment and chemical cleaning. They emphasized that understanding the specific fouling mechanisms is crucial for developing effective mitigation strategies. This article relates closely to the optimization of membrane fouling and filtration, as it highlights the importance of tailored approaches to manage fouling in desalination processes, ultimately improving system efficiency and reducing operational costs.

Jin *et al.* (2020) discussed the practical applications of fouling indices in seawater reverse osmosis (SWRO) plants. Fouling indices are primarily used to assess pretreatment process efficiency and predict fouling behaviour in the reverse osmosis (RO) process. Membrane pretreatment, particularly using ultrafiltration (UF), is favoured for reducing fouling potential compared to other methods like dissolved-air flotation (DAF). Studies show that UF consistently produces water with low fouling potential, meeting RO standards. Fouling indices also aid in determining chemical dosing for pretreatment, especially during events like harmful algal blooms (HABs), which can affect water quality and increase operational challenges.
Recent developments focus on utilizing membrane fouling indices (MFI) to predict transmembrane pressure (TMP) increases in RO. MFI can forecast TMP increments, essential for effective cleaning processes based on the understanding of cake-layer resistivity.
Efforts to improve fouling indices include using membranes with smaller pore sizes to capture a wider range of foulants and considering hydrodynamic conditions like RO processes. Multiple fouling indices are proposed to provide detailed insights into feed-water characteristics.

4 Pre-Treatment Strategies and Optimization

Pretreatment strategies are essential processes used to prepare water for subsequent treatment stages, particularly in systems involving membrane filtration, reverse osmosis (RO), and other advanced water treatment technologies. These strategies aim to remove contaminants that could cause fouling, scaling, or other operational issues in downstream processes. Below are some common pretreatment strategies along with their optimization techniques.

i. Physical Pretreatment

Physical pretreatment methods involve the removal of larger particles and debris from water before it undergoes further treatment. Common techniques include:

- Screening: This method uses screens to filter out large solids and debris, protecting downstream equipment from damage.
- Sedimentation: Allowing particles to settle out of the water by gravity can effectively reduce turbidity and suspended solids.
- Filtration: Sand filters or multimedia filters can remove finer particles, enhancing water quality before it reaches more sensitive treatment processes.

Optimization: Regular maintenance and monitoring of filter performance can help ensure optimal flow rates and reduce the frequency of cleaning, thereby extending the lifespan of the filtration media (Guo *et al.*, 2010).

ii. Chemical Pretreatment

Chemical pretreatment involves adding chemicals to alter the properties of contaminants, making them easier to remove. Key methods include:

- Coagulation and Flocculation: Coagulants (e.g., aluminium sulphate) destabilize suspended particles which allows them to aggregate into larger flocs that can be removed through sedimentation or filtration. This process is particularly effective in removing colloidal materials and organic matter (Matilainen *et al.,* 2010).
- pH Adjustment: Adjusting the pH of water can enhance the effectiveness of coagulation and reduce the potential for scaling in downstream processes.
- Disinfection: Chemicals such as chlorine or ozone can be used to inactivate microorganisms, reducing biological fouling in membrane systems.

Optimization: The dosage of coagulants and the timing of chemical additions should be carefully controlled based on real-time water quality monitoring to minimize chemical use while maximizing treatment efficiency (Matilainen *et al.,* 2010).

iii. Membrane Pretreatment

Membrane pretreatment specifically targets the removal of contaminants that can foul membranes. Techniques used for membrane pretreatment include:

- Microfiltration (MF) and Ultrafiltration (UF): These processes use membranes to remove suspended solids, bacteria, and some viruses before water enters RO systems. They are effective in reducing fouling potential and improving permeate quality (Huang *et al.,* 2008).
- Advanced Oxidation Processes (AOPs): AOPs can break down organic contaminants and enhance the removal of natural organic matter (NOM), which is critical for protecting membrane integrity.
- Optimization: Regular backwashing and chemical cleaning of membranes can help maintain performance and extend their operational life. Additionally, integrating MF or UF with RO systems can significantly reduce fouling and improve overall system efficiency (Huang *et al.*, 2008).

iv. Hybrid Pretreatment Systems

Combining different pretreatment methods can enhance overall treatment effectiveness. For example, integrating coagulation with membrane filtration can improve the removal of NOM and reduce fouling in downstream processes.

Optimization: Tailoring the hybrid system to the specific characteristics of the feed water, such as its turbidity and organic content, can lead to better performance and lower operational costs (Guo *et al.,* 2010: Matilainen *et al.,* 2010).

Several pretreatment methods and approaches have been used for different applications. A review of some of the applications of these pretreatment methods is provided as follows:

Anis *et al.* (2019) provided an extensive review of various pretreatment technologies specifically designed for reverse osmosis systems. The authors discussed conventional methods such as coagulation, flocculation, and media filtration, alongside advanced techniques like microfiltration and ultrafiltration. They emphasized that effective pretreatment is crucial for mitigating fouling and scaling, which can significantly impact RO performance. The article also highlighted the importance of selecting appropriate pretreatment methods based on feed water quality and operational conditions, aligning with the need for optimization in water treatment processes to enhance efficiency and reduce costs

Koo *et al*. (2021) affirmed that reverse osmosis (RO) desalination which is crucial for high-quality drinking water, faces membrane fouling challenges, impacting performance and lifespan. Various strategies, including pre-treatment, membrane modification, and operational optimization, were explored and among these, novel feed spacer designs in spiral wound modules (SWM) showed promise in mitigating fouling. Traditional mesh spacers balance mass transfer enhancement with increased pressure loss aimed to optimize feed spacers for maximum flux and fouling control.

In addition to this, two approaches to optimizing feed spacer geometry were explored by Koo *et al.* (2021) which are enhancing conventional mesh design and developing novel designs. While modifications to conventional mesh spacers have improved performance, they still present limitations. Novel designs, such as sinusoidal channels or zigzag filaments, offer alternatives but face challenges in fabrication and integration. 3D printing technology was proposed as a solution, allowing for the fabrication of complex spacer designs with improved feasibility for integration into SWMs. This study focused on improving a sinusoidal spacer design using 3D printing. Structural integrity and stability are enhanced by introducing transverse filaments. Experimentation evaluates water flux, channel pressure loss, and fouling mitigation capabilities and the results indicate comparable membrane flux for conventional and slanted (SL) spacers, with straight (ST) spacers showing slightly lower flux. These findings underscore the potential of 3D printed spacers in enhancing RO processes.

Also, Niu *et al*. (2022) focused on utilization of AI techniques in membrane filtration, particularly focusing on artificial neural networks (ANN) as the predominant algorithm for predicting membrane fouling. The hydrodynamic condition within the flow spacer-filled channel is influenced by the geometry of the elements. Linear crossflow velocity is determined by parameters such as bulk flowrate, channel dimensions, unwound channel count, and spacer voidage.

Placement of Energy Recovery Devices (ERD) impacts pressure recovery. The concentrate-to-feed ratio (R) in ERD affects pressure recovery proportionally. Introducing an Inter-Stage ERD (ISERD) before the second stage optimizes pressure recovery compared to standard configurations resulting in enhanced recovery and improved permeate quality. However, for recovery levels below 50%, the standard configuration may be more energy-efficient than ISERD configurations, minimizing energy loss.

Over the past two decades, various AI algorithms including ANN, search algorithms, fuzzy logic (FL), genetic programming (GP), and support vector machines (SVM) have been effectively employed to predict membrane fouling in different membrane systems. These techniques utilize factors influencing fouling, such as operating conditions, water quality parameters, membrane types, and biomass properties, as inputs. Among these algorithms, ANN stood out for its flexibility and adaptability in predicting membrane fouling across diverse filtration systems.

Najid *et al*. (2022) concentrated on significant challenges in reverse osmosis (RO) membrane facilities leading to reduced permeate production and increased solute passage. Cleaning is crucial to mitigate fouling and maintain membrane permeability, but frequent cleaning can make RO systems less robust, resulting in longer downtime and membrane damage. New membrane technologies, such as aromatic polyamide thin-film composite (TFC) membranes, aim to prevent fouling and improve long-term performance. Fouling modelling helps understand its effects on membrane resistance and water permeability. Fouling mechanisms include biofouling, organic fouling, colloidal fouling, and scaling, each requiring tailored mitigation strategies.

Razali *et al.* (2023) investigated the optimization of coagulation and flocculation processes as pretreatment strategies for membrane filtration systems. They present experimental results demonstrating how varying coagulant types and dosages can significantly affect the removal of turbidity and organic matter, which are key contributors to membrane fouling. The findings indicate that optimized coagulation can lead to improved permeate quality and reduced fouling rates, reinforcing the importance of effective pretreatment strategies in enhancing the overall performance of membrane-based water treatment systems.

Tapiero *et al.* (2023) utilized a membrane cut-off from a SWC6-LD spiral wound element for brackish water reverse osmosis processes at Glauben Ecology Spa in Chile. The study identified areas most affected by contamination, particularly on the input side of the membrane. The outer membrane sheet and spacer experienced significant damage due to incrustations and fouling, while the inner membrane sheet and spacer showed less degradation.

Water samples were analysed for conductivity, total dissolved solids, pH, hardness, nitrate, phosphate, and iron concentrations. The reverse osmosis process includes pre-treatment with multimedia filters and acid/basic agent dosage but lacks anti-scaling agents.

Two software programs were used to calculate scaling potential based on water composition data.

These programs estimate the saturation ratio of various compounds and predict scale development. Microstructural Characterization, Electron microscopy and Fourier transform infrared spectroscopy (FT-IR) were used to analyse membrane damage and fouling layers. Weight loss on ignition tests and thermogravimetric analysis (TGA/DTG) determined the decomposition temperature and organic/inorganic percentages in the membranes.

The autopsy highlighted irregular fouling deposits with thin thickness, while membrane spacers remained unobstructed. The water sample extracted from the SWC6-LD membrane element exhibited cloudy appearance with suspended orange to light brown material and a slight metallic odour. A table presented the physicochemical characterization of this water sample, revealing high total dissolved solids, slightly alkaline conditions, high hardness (both total and carbonate), and moderate to high concentrations of nitrate, phosphate, and iron. The presence of hard water and alkalinity could lead to scaling issues, while nitrate and phosphate concentrations may be attributed to previous chemical dosages. SEM/EDX analysis of solids obtained from boiling the water sample revealed amorphous and irregular crystals with elemental compositions including Cl, O, Na, Fe, Ca, Mg, Si, and Al, indicating the potential for fouling.

Localized visual inspection of membrane components revealed high concentrations of fouling material, particularly on the surfaces of spacers and membranes. The roughness of the membrane surface and spacer threads contribute to fouling deposition. Cleaning by sonication partially removed fouling material but some areas persisted due to surface imperfections.

The Fujiwara test was used to assess the impact of oxidizing agents on membrane components, revealing a slight colour change indicating degradation. Further analysis via FT-IR spectroscopy identified fouling layers composed of polysaccharides, proteins, and silica. Scanning electron microscopy (SEM/EDS) confirmed the presence of fouling materials, while thermal analysis showed predominantly inorganic fouling. Weight loss on ignition tests supported these findings, indicating heavy organic fouling. Thermogravimetric analysis revealed multistage decomposition processes, with organic material mainly responsible for fouling. The study highlights the inevitability of fouling in reverse osmosis membranes and emphasized the need for effective pretreatment processes to control contaminants and prevent membrane degradation. Additionally, autopsy procedures on discarded membranes are recommended for maintenance to identify fouling causes and process failures.

Pratofiorito *et al.* (2024) designed Flat sheet membrane modules (FMM) to mimic flow conditions within the feed channel of spiral wound modules. Extra low energy (XLE) membrane coupons were placed in the channel atop a permeate spacer, with a 28 mil thick feed spacer inserted. Linear flow velocity was maintained at 0.2 m/s. Biofilm growth was monitored using OCT, with experiments showing permeability decline over time.

Biofilm detection was conducted using a smooth surface sensor in parallel with FMM. While no biofilm attachment was detected on the sensor, significant biofilm formation was observed in the FMM feed channel. This highlights the potential of biofilm sensors as early warning tools for RO systems.

5 Monitoring and Predictive Maintenance

The monitoring and predictive maintenance of reverse osmosis (RO) systems have evolved significantly with the integration of advanced technologies and hybrid modelling approaches. Recent studies have demonstrated the effectiveness of combining traditional mechanistic models with data-driven techniques to enhance system performance prediction and maintenance scheduling. From comprehensive monitoring systems using embedded electronics to sophisticated hybrid models incorporating machine learning, these developments represent significant advances in RO system management (Srivastava *et al.,* 2018; Gaublomme *et al.,* 2023; Teng and Ng, 2024).

Srivastava *et al.* (2018) proposed a scheme which introduces a comprehensive system for monitoring reverse osmosis (RO) plants, aiming to minimize information loss and distribute complexity across different layers. It involved parameters monitoring, data storage, and computational algorithms at various levels, ensuring real-time data collection and analysis. Key components include an embedded RO plant status monitoring unit interfaced with off-theshelf sensors, a customized hardware platform integrated with a quad-core ARMv8 processor-based microcontroller unit for data acquisition and processing, and a classical Bluetooth module for communication with a smartphone-based app. Data collected at the local level are transferred to the cloud for centralized monitoring and analysis, facilitated by a dedicated Android app and Google Firebase platform. Additionally, a 2G GSM module serves as a backup option for data communication. The system is designed to be modular, user-friendly, and cost-effective, facilitating early fault prediction and predictive maintenance for RO plants. Algorithms, particularly based on Artificial Neural Networks (ANNs), are employed for predicting membrane fouling and scaling events, aiding in timely maintenance actions. Field trials demonstrate the system's effectiveness in real-world scenarios, providing early fault detection and predictive maintenance guidance to operators.

Gaublomme *et al.* (2023) experimented on a full-scale reverse osmosis (RO) installation operated by the water utility FARYS in Belgium, serving a cereal processing and food producing company. The RO installation comprises four parallel treatment lines, each consisting of a double-pass RO (DPRO) system followed by an electrode ionization (EDI) step. The RO membrane modules are of type AK-440 (AK HR Series, SUEZ, France). Each line produces demineralized water at a rate of 23 to /h with an average DPRO recovery of about 82% and fixed EDI recovery of 95%, operating around 50% of the time. The feed water is drinking water sourced from the Albert Canal, prone to seasonal temperature and conductivity fluctuations.
Data collection involved continuous monitoring via a Supervisory Control and Data Acquisition (SCADA) system for variables like pressure, flow rate, conductivity, temperature, and pH. Offline data on calcium concentration was collected every two weeks from a water tower. Data preprocessing included filtering, interpolation, and subsampling to prepare it for modelling.
The study also developed a mechanistic solution-diffusion model to predict RO performance based on feed pressure, flow rate, conductivity, and temperature. A fouling model predicting additional membrane resistance due to fouling was integrated into the model. Two types of data-driven fouling models were considered: a simple mechanistic flux-based model and two time series models (linear ARIMAX and non-linear RNN-LSTM). The best performing fouling model was combined with the solution-diffusion model into a hybrid model, incorporating predicted additional membrane resistance into key parameters affected by fouling.
The hybrid model's predictions were compared with those of the original mechanistic model using a temperature correction factor (TCF). This comprehensive approach aims to better understand and predict fouling behaviour in RO systems, crucial for efficient operation and maintenance.
The data preprocessing phase involved several steps to prepare the dataset for analysis. The initial dataset consisted of 2,563,584 time series data points from 17 sensors over 58 months with a reading frequency of 1 minute. Periods where the installation was not operational or underwent cleaning were removed, amounting to 47% and 2% of the data, respectively. Outliers were filtered and filled through interpolation, resulting in 0.4% to 2% of the data being filled depending on the variable. Most outliers were successfully removed, and interpolated data of two-weekly offline calcium measurements were presented.
The calculated additional membrane resistance over time showed an increase due to fouling, with reversible fouling indicated by drops after cleaning-in-place (CIP) events and irreversible fouling over the installation's lifespan.
The data-driven fouling models were developed using input variables such as feed characteristics, concentrate flow rate, recovery, and CIP occurrences. Different data-driven models like ARIMAX and RNN-LSTM were evaluated, with the latter showing the best performance in predicting membrane resistance evolution over time. However, challenges remained in accurately capturing the impact of CIP events and unexpected incidents, such as a ship incident affecting feed water composition.
The hybrid model combined the best performing RNN-LSTM model with a mechanistic solution-diffusion model to predict system performance considering variabilities in feed and operational settings. The hybrid model proved effective for real-time analysis, operational decision-making, and advanced control strategies, providing a basis for the development of digital twins and soft sensors for fouling prediction.

Teng and Ng. (2024) combined mechanistic and data-driven models to predict fouling in reverse osmosis (RO) membrane systems using real operation data. Raw data from a plant operation period were pre-processed to remove outliers and system stop points. Parameters like inlet water quality, pressure, and conductivity were analysed, with minimal outliers replaced to ensure data quality. Curve fitting techniques were applied to estimate key parameters related to membrane fouling, balancing accuracy and information retention. Genetic algorithms aided in finding optimal fits, demonstrating accurate prediction of transmembrane pressure (TMP) values. Long short-term memory (LSTM) models were then employed to predict future parameter values, which were used in an adsorption model to forecast TMP. The integrated model showed comparable or slightly better performance than pure data-driven models, indicating its reliability in predicting fouling behaviour over time. The study suggests a transition from pore blockage to cake filtration as the dominant fouling mechanism, supported by observed trends. Though the model's physical parameters lack direct meaning, they offered insights into fouling behaviour and may aid in refining understanding with further research.

This study by Tchobanoglous *et al.* (2019) focused on the development of a real-time monitoring and control system for RO processes. The authors describe a framework that utilizes various sensors to monitor critical parameters such as pressure, flow rate, and water quality. By implementing a feedback control loop, the system can adjust operational conditions dynamically to optimize performance and mitigate fouling. The findings demonstrate that real-time monitoring leads to improved system efficiency and reduced maintenance needs, aligning with the importance of proactive management strategies in RO systems highlighted in previous research.

Liu *et al.* (2020) investigated the application of machine learning algorithms for predictive maintenance in membrane filtration systems, focusing on RO technology. The authors present a comparative analysis of different machine learning models, such as support vector machines and neural networks, to predict membrane fouling and performance degradation. The study shows that these models can accurately forecast maintenance requirements based on historical operational data, enabling timely interventions. This research emphasizes the potential of data-driven approaches in enhancing predictive maintenance, complementing the hybrid modelling strategies discussed in earlier studies.

Further, Khamis *et al.* (2021) reviewed integrated monitoring and control systems in water treatment, including RO technologies. The authors highlight advancements in sensor technologies and data integration techniques that allow for comprehensive system oversight. The study revealed that operators can better manage operational parameters and predict system failures by combining data from multiple sources, including remote monitoring and automated control systems. This integration of monitoring and control is crucial for optimizing RO performance, reinforcing the trend towards more sophisticated management techniques in water treatment processes.

Zhang *et al.* (2022) explored the use of predictive analytics in membrane filtration systems, specifically focusing on RO applications. The authors utilize historical data to develop predictive models that forecast system behaviour and maintenance needs. The study identified key indicators of potential fouling and performance issues by analysing patterns in operational data. The results suggest that implementing predictive analytics can significantly reduce downtime and maintenance costs, aligning with the ongoing theme of integrating advanced technologies for improved management of RO systems.

Finally, Kim *et al.* (2023) investigated the use of acoustic emission (AE) technology for condition monitoring of RO membranes, demonstrating that AE can effectively detect early signs of fouling and structural degradation. The study affirmed that integrating AE monitoring with traditional performance metrics can enhance predictive maintenance strategies, which allows for more timely and informed decision-making. This innovative approach contributes to the growing body of research on advanced monitoring techniques for optimizing RO system performance.

6 AI and Machine Learning Integration

Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as powerful tools for simulating intelligent behaviour in computers, and for numerous applications (Ajayi, 2023, Ajayi *et al.*, 2024a, Ajayi *et al.*, 2024b), including the provision of predictive capabilities to better comprehend and manage membrane fouling. Intelligent models,

including Artificial Neural Networks (ANNs), Fuzzy Logic (FL) models, and Genetic Programming (GP), aim for higher accuracy in predicting membrane fouling indices compared to mechanistic models.
Furthermore, intelligent optimization techniques like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are utilized to optimize filtration processes and mitigate membrane fouling, ultimately reducing treatment costs. Hybrid models, combining AI/ML with mechanistic models, enhance accuracy and understanding of fouling mechanisms.
In addition to this, cluster analysis helps in identifying different potential causes of fouling and grouping wastewaters for effective control and management of membrane fouling. Image recognition techniques, particularly in machine vision applications, aid in identifying features related to membrane fouling.
Automatic selection of relevant attributes in data assists in building accurate predictive models by removing irrelevant variables, thereby contributing to better predictive accuracy.

Bagheri *et al.* (2019) discussed various aspects related to membrane fouling, modelling, optimization, and control techniques, particularly focusing on the role of AI and ML in addressing this issue. The study emphasized the significance of understanding and addressing the various factors contributing to membrane fouling, such as operating conditions, biomass characteristics, and membrane properties. Mechanistic models like Hermia's model focus on pore blocking mechanisms to predict flux decline and enhance understanding of fouling phenomena during filtration.

The application of ML techniques in water and wastewater treatment were outlined by Mathaba and Banza (2023) with emphasis on five main issues addressed by ML: clustering, regression, dimensionality reduction, and classification. Various ML techniques such as artificial neural networks (ANN), deep learning (DL), random forests (RF), and support vector machines (SVM) are utilized for nonlinear classification and regression analysis, with ANN and DL being prominent due to their ability to mimic animal neural networks. ML models are employed in predicting water quality parameters, adsorption processes, membrane-filtration processes, and water-quality management, aiming to optimize treatment processes and enhance efficiency. Challenges in AI and ML application include explainability, data management, reproducibility, and lack of benchmarking and standardization (Ajayi, 2023).

Habieeb *et al.* (2023) discussed the global issue of water scarcity and the importance of desalination in addressing this challenge. Desalination, which is the process of removing salt and minerals from water, is crucial for providing clean water for various purposes. Two main methods of desalination; thermal desalination, and membrane desalination, were highlighted.
The focus then shifts to membrane desalination, particularly Reverse Osmosis (RO), which purifies water by removing salts and contaminants through a semi-permeable membrane. The process of RO and its key parameters such as osmotic pressure, permeate water, and salt passage percentage are explained.
The integration of AI techniques in desalination, specifically RO systems, was also explored. AI offers benefits such as improved productivity, reduced energy consumption, predictive maintenance, optimization of operating parameters, and better control of water quality.
The study highlighted the importance of expanding datasets for AI models, exploring hybrid AI technologies, and continuously updating AI techniques to keep up with advancements in membrane systems. It concludes by emphasizing the promising role of AI in revolutionizing water desalination processes, addressing global water scarcity, and improving access to clean drinking water.

Wang *et al*. (2024) affirmed that understanding the influencing factors and mechanisms of membrane fouling is crucial for developing accurate predictive models. Classical mathematical models and artificial intelligence (AI) models play significant roles in predicting and mitigating fouling. Mechanisms such as classic blocking, depth filtration, and microscopic models help explain fouling behaviour. Mathematical models like the tandem resistance model are commonly used to predict fouling by simulating the fouling process. AI models, on the other hand, utilize interdisciplinary knowledge to recognize patterns and make intelligent decisions, which is advantageous in predicting fouling parameters and identifying influential factors. Challenges in AI prediction include adapting to different membrane types and feed solutions, but AI technology has shown significant prospect for developing early warning and monitoring systems to combat fouling effectively. Compared to conventional models, AI models offer higher prediction accuracy and adaptability which makes them suitable for intelligent control systems in large-scale application (Ajayi, 2024).

Chang *et al.* (2024) focused on the application of artificial intelligence (AI) in wastewater treatment and water recycling methods using vast amounts of data, particularly through image recognition and natural language processing. This approach utilizes water quality and operating parameters of water treatment systems, combined with big data collection, to train AI models. These models analyse wastewater composition and generate decision results, enabling intelligent control of the system. Initially, monitoring systems with intelligent data collection terminals are employed during facility establishment. These terminals extract real-time data on water quality and equipment operations, which are transmitted to web access through wireless remote intelligent data collection terminals. The data collected are transformed into management dashboards through the WISE-PaaS Industrial IoT cloud platform, enabling visualization and AI intelligent wastewater management.

Membrane Bioreactors (MBRs) combine activated sludge with membrane separation technology thereby offering high-efficiency effluent, high load capacity, and a small footprint. AI-integrated technologies, including ANN and GA can accurately predict membrane fouling for membrane fouling control in wastewater treatment. ANN mimics animal neural networks to perform distributed and parallel information processing, while GA can optimize conditions of reverse osmosis wastewater treatment processes.

AI technologies applicable to water treatment and water recovery methods include massive data analysis, image recognition, and natural language processing. These applications enhance precision, efficiency, and responsiveness in managing complex wastewater treatment processes.

With global water resources dwindling and stricter water management regulations, integrating and applying water treatment technologies with innovative intelligent approaches is essential.

In theoretical terms, the study aligns with Systems Theory, Data-Driven Fault Detection and Diagnosis, and Process Systems Engineering theories. AI applications actively monitor equipment, predict maintenance needs, and ensure water consistently meets quality standards. Tailoring AI capabilities to specific needs advances circular economy principles and promotes sustainability and environmental preservation.

Finally, Osman *et al*. (2024) reviewed the application of machine learning to enhance the efficiency of membrane filtration processes across various sectors such as energy, gas separation, and water treatment. Specifically focusing on reverse osmosis, nanofiltration, pervaporation, and the removal of pollutants, pathogens, and nutrients, as well as gas separation for carbon dioxide, oxygen, and hydrogen, fuel cells, biodiesel, and biogas purification. The study highlighted significant improvements in performance and efficiency achieved through the integration of machine learning, resulting in specialized membranes with remarkable potential for diverse applications. Notably, membrane gas separation techniques aided by ML contribute to carbon capture and the purification of industrial gases, thereby supporting efforts to reduce carbon dioxide emissions.

7 Performance Evaluation and Prediction

Membrane fouling prediction and performance evaluation in reverse osmosis (RO) systems represent critical aspects of water treatment technology. Recent advances in both experimental methodologies and predictive modelling have enhanced our understanding of membrane fouling mechanisms and their impact on system performance. This comprehensive review examines various approaches to performance evaluation, fouling prediction tools, and experimental protocols that have been developed to optimize RO system operations (Koo *et al.,* 2013; Mohammed *et al.,* 2024).

Koo *et al.* (2013) discussed the importance of understanding various types and causes of fouling in reverse osmosis (RO) and nanofiltration (NF) membranes for the development of a fouling prediction tool. It starts with an overview of membrane fouling mechanisms, including colloidal, organic, inorganic, and biological fouling. The interactions of different foulants with membrane surfaces are explained, along with methods for assessing membrane fouling severity.

It emphasized the significance of pore size and membrane structure in determining fouling susceptibility, as well as factors like concentration polarization and membrane properties. The text also covers advanced techniques such as Field Emission Scanning Electron Microscopy (FESEM), Atomic Force Microscopy (AFM), and Fourier Transform Infrared (FTIR) Spectroscopy for analysing fouling behaviour and membrane-solute interactions.

The discussion then explored fouling prediction tools, focusing on indices like Silt Density Index (SDI), Modified Fouling Index (MFI), and Mini Plugging Factor Index (MPFI). It explains their principles, measurement methods, and how they are influenced by operating conditions and membrane properties. Additionally, it mentions the early development of fouling indices and advancements in portable SDI testers for real-time fouling potential measurement.

The study revealed that surface waters contain particulate matter that affects water purity, but SDI, a commonly used index, has deficiencies. It lacks a linear relationship between particulate matter and foulant concentration, and it does not consider factors like temperature, pressure, and membrane resistance. SDI may not accurately represent membrane fouling behaviour.

MFI addresses SDI limitations by incorporating membrane productivity and considering pressure and temperature effects. However, MFI measurement is more complex than SDI. Studies show that MFI values increase with decreasing membrane pore size, indicating the presence of smaller colloids. UF membranes are found more effective than MF due to their ability to retain smaller particles.

Minier-Matar *et al.* (2024) designed an experimental setup for evaluating reverse osmosis (RO) performance involved a custom-built bench scale unit. The setup circulated the feed solution through a closed loop containing a high-pressure pump and an RO membrane cell. The pressure was controlled using a back-pressure regulator, and temperature was maintained using a refrigerated and heating circulator. A proportional-integral-derivative (PID) controller adjusted pump speed to maintain constant pressure and flow rate. Two feed tanks allowed switching solutions without depressurizing the membrane, facilitating benchmark tests. Permeate flow and conductivities were measured, and water flux was calculated. Operational challenges like flow rate variabilities and temperature increases were addressed during the startup phase.

To report effective flux normalized by driving force, a series of steps were followed: estimating feed salinity from conductivity, calculating osmotic pressure, determining effective driving force, and finally calculating normalized flux. Measurement errors were minimized by frequent data acquisition. RO performance was modelled using IMS Design software, which simulates RO systems using specific membrane characteristics. A protocol resembling full-scale conditions was followed, including membrane compaction, benchmark tests with synthetic solution, and continuous monitoring during various test stages.

Various chemicals were used in the experiments, and laboratory analyses included ion chromatography, inductively coupled plasma, pH/conductivity measurements, and Fourier-transform infrared analysis. For organic characterization, a liquid chromatography system with an organic carbon detector was employed to fractionate soluble organics based on hydrophilicity and hydrophobicity.

The system was calibrated using potassium hydrogen phthalate standards, and duplicate analyses were performed for accuracy. This comprehensive approach allowed detailed evaluation of RO membrane performance and characterization of organic compounds in the feed water.

Bench-scale experiments was conducted to evaluate the performance of reverse osmosis (RO) membranes in treating industrial wastewater, focusing on the impact of activated carbon fiber (ACF) pretreatment on membrane fouling. Flux trends, organics rejection, and membrane surface characteristics were analysed using two different water samples: ACF feed and RO feed water. Antiscalant and biocide were added to the ACF feed to prevent scaling and biological fouling. Synthetic NaCl solutions were initially tested to validate unit performance. Results showed an immediate decline in flux with ACF feed due to organics, while stable performance was observed with RO feed after ACF pretreatment. FTIR analysis confirmed fouling in ACF feed experiments. Organic characterization revealed ACF's ability to remove >50% of hydrophobic organics. Bench-scale results closely matched full-scale plant data, validating the testing protocol. LC-OCD methodology coupled with bench-testing may optimize wastewater treatment processes.

The study by Mohammed *et al.* (2024) focused on predicting salt rejection in a Seawater Reverse Osmosis (SWRO) plant in the United Arab Emirates using machine learning models. They utilized data collected from January 1st, 2018, to November 16th, 2021, comprising 1243 samples with various operational and water characteristic parameters. Two sets of ML models, including non-ensemble models and ensemble models, were employed for prediction, and extensive data preprocessing and evaluation techniques were applied. The XGBoost ensemble model emerged as the best-performing model for predicting salt rejection, demonstrating high accuracy and robustness. The study highlighted the importance of considering a comprehensive set of parameters and employing advanced machine learning techniques for predictive modelling in complex membrane systems like RO.

On the other hand, the discussion on membrane fouling mechanisms, assessment techniques, and the development of fouling prediction tools, particularly focusing on the Modified Fouling Index (MFI) and its potential to accurately predict fouling propensity in RO processes. While MFI offers improvements over other methods like Silt Density Index (SDI), its limitation in assessing diverse feed waters is noted. The incorporation of a Crossflow Sampler (CFS) into MFI measurements is proposed to enhance accuracy by mimicking RO crossflow conditions. The article emphasized the importance of developing reliable fouling indices for accurately predicting membrane fouling and underscores the need for further research to develop comprehensive prediction tools applicable across different water sources and membrane systems.

9 Nanoparticle-Induced Fouling

In reverse osmosis (RO) membrane systems, the interplay between various foulants presents a significant challenge for maintaining optimal performance. The study by Yang *et al.* (2024) provides crucial insights into how nanoparticles (NPs) influence membrane fouling dynamics, particularly focusing on their synergistic interactions with silica scaling and humic acid (HA) fouling. Understanding these interactions is essential as the presence of NPs in water sources becomes increasingly common, potentially affecting the efficiency and longevity of RO membrane systems.

Yang *et al.* (2024) investigated the fouling potential of reverse osmosis (RO) membranes induced by nanoparticles (NPs) and examined the synergistic effects of NPs with silica scaling and humic acid (HA) fouling. Three types of NPs were studied: polystyrene (PS), carboxyl group decorated PS (PS-COOH), and amino group decorated PS (PS-NH2). The results showed that the surface potential of NPs played a crucial role in determining the scaling and fouling tendency of RO membranes. While the adsorption and deposition of NPs on the membranes induced negligible flux declines (1–6%), they changed the physicochemical properties of the membrane surface, making it more prone to fouling, especially in the case of positively charged NPs.
In the presence of PS-NH2, which exhibited positive surface potential, membrane fouling was significantly accelerated. PS-NH2 facilitated silica scaling by providing a heterogeneous interface required for silica nucleation, leading to increased flux decline rates. Similarly, HA fouling was expedited in the presence of positively charged NPs due to electrostatic attraction and ligand exchange mechanisms. The study also investigated the thermodynamic parameters of the interaction between PS-NH2 and silicates/HA using isothermal titration calorimetry (ITC), showing that stable complex pollutants were spontaneously formed via electrostatic interactions and non-covalent binding forces.

10 Identified Research Gaps

Based on this review, the following research gaps are identified.

1. Refinement of the fouling detection method and development of online measurement systems for real-time monitoring of membrane fouling
2. Challenges in accurately predicting fouling potential, such as variations in hydrodynamic conditions and membrane pore sizes.
3. Considering the importance of understanding the molecular-level mechanisms driving membrane fouling to design effective treatment processes and materials for water purification and reuse applications, there is need for advanced characterization techniques because they play a crucial the development of innovative solutions to mitigate membrane fouling.
4. Despite advancements, there is a need for standardization and practical applicability

of fouling indices in real-scale RO plants. while fouling indices like MFI show promise in assessing fouling potential and optimizing RO plant operations, further research and data accumulation are needed to establish reliable guidelines for their application in real-world scenarios.

5. Development of explainable models, managing data effectively, integrating causality into ML models, and ensuring transparency and reproducibility are all subjects of ongoing studies in membrane fouling prediction and optimization.
6. Implementation of advanced filtration systems to convert wastewater into drinking water, transforming industrial practices to be more sustainable and environmentally friendly.
7. Finally, exploring the interactions of NPs with other scalants and foulants, as well as their implications for membrane-based desalination processes.

11 Conclusion

Addressing membrane fouling remains a critical challenge in optimizing reverse osmosis processes for water treatment. The findings from various studies underscore that different fouling mechanisms—ranging from organic and particulate fouling to biofouling—require tailored approaches for effective mitigation. Advanced modelling techniques and characterization methods have proven essential for understanding fouling dynamics and improving predictive capabilities. Furthermore, pre-treatment strategies such as coagulation significantly enhance feed water quality and reduce operational costs associated with membrane cleaning. The promising role of artificial intelligence in predicting fouling behaviour indicates a future direction for research that could lead to more efficient membrane filtration systems. Continued exploration of novel materials, designs, and operational strategies will be vital in advancing the field and ensuring sustainable water treatment solutions.

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